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Web-Based Smart Irrigation System Using Machine Learning

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A B S T R A C T

The Smart Irrigation System (SIS) represents an advanced approach for controlling, monitoring, and automating irrigation processes by incorporating artificial intelligence techniques, particularly Machine Learning (ML) methods. Although several ML models have been applied within SIS, there has been limited effort to systematically examine the empirical evidence related to these models. In addition, ML-based SIS solutions often encounter various challenges and raise concerns that require further investigation. This paper provides a systematic literature review of ML-driven SIS, offering a comprehensive and unbiased overview of existing research in this domain.

A total of 55 studies published between 2017 and 2023 were analyzed, identifying nine widely adopted ML models. The review is structured around four key analytical dimensions: the type of ML technique used, estimation accuracy, comparative analysis of models, and the context of estimation. The results demonstrate that ML techniques applied in SIS show superior performance when compared to traditional methods. However, despite their advantages, the adoption of ML models in smart irrigation remains limited, indicating the need for further research to achieve more robust and generalizable outcomes. Based on these findings, the study also proposes future directions and guidelines to assist researchers and practitioners in understanding the key contributions, challenges, and advancements in this evolving field.

Index: Smart Irrigation System (SIS), Machine Learning (ML), Precision Agriculture, Internet of Things (IoT), Soil Moisture Prediction, Water Resource Optimization, Sustainable Agriculture, Predictive Modeling

1. Introduction

The world knows emergency problems, foremost among them being the scarcity of fresh water. Around 70 % of freshwater used in agricultural activities such irrigation and the supply nutrient for plant growth. The demand for freshwater is escalating with the increasing food demand of a fast-growing population [1]. The optimal solution for this problem is switching from traditional irrigation methods to new irrigation systems by including new technologies such internet of thing (IoT), machine learning (ML), wireless sensor network (WSN) giving birth to the term smart irrigation systems (SIS). This latter allows us to improve the irrigation decision-making and monitoring water systems to enhance crop productivity [2].

SIS aims to prevent both under-irrigation and over-irrigation, ensuring optimal crop yields. Many types of crops have specific water requirements that vary throughout their growth stages. Also, SIS Overcomes hurdles soil erosion and crop specific irrigation problem. Efficient Irrigation guaranties a sustainable use of water, this indicates that SIS is not trivial task, instead, it composes of several complicated steps [3]. Globally, the main purpose behind smart irrigation systems is that enhance agricultural productivity at the same time reducing the environmental impact of crops.

One of the most used technics in SIS is Machine Learning. It addresses the question of how to build a computer system that improves automatically through experience [4,5]. ML techniques re known for (i) their capacity to independently tackle significant nonlinear challenges by utilizing datasets from various origins, and (ii) their flexibility in integrating fresh data to enhance the accuracy (Mohammed [6,7]). They are being used in the context of studying smart irrigation to provide users with better recommendations and help constructing powerful ML models.

ML techniques are integrated in many fields, they are used in irrigation field to estimate soil moisture content, to estimate the reference of evapotranspiration, to improve energy management performance and to Predict water table depth. Generally speaking with ML we can provide decision-making in irrigated agriculture by using meteorological and soil data, also we can contribute to sustainability efforts by conserving water resources. By precisely delivering water where and when it is

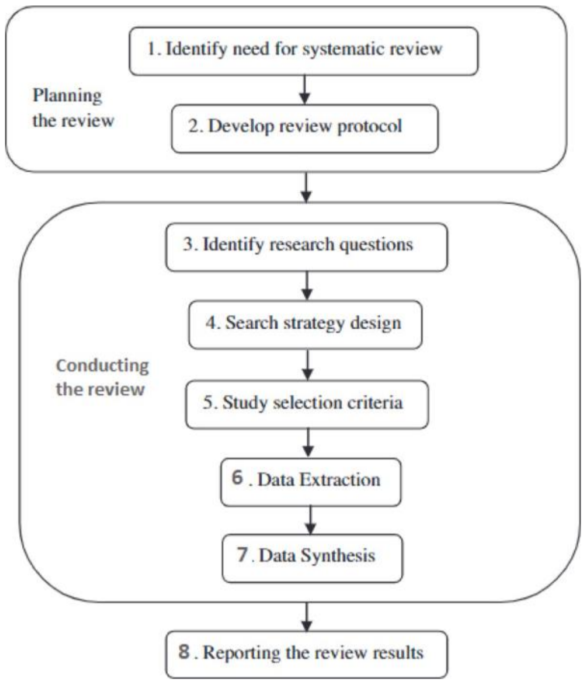

Fig. 1. Systematic review process.

needed, these systems reduce unnecessary irrigation, mitigate water scarcity issues, and promote efficient water management practices in agriculture. However, the ML discipline does not have a definite classification scheme for its algorithms, mostly due to the number of paradigms and the uncertainties introduced in the literature ([8,7]b; [9]). Subsequently, it becomes difficult and confusing to choose an ML algorithm that fits one's need when developing a smart irrigation computational model.

In order to gain a comprehensive understanding of the existing research on the utilization of machine learning (ML) in smart irrigation system, we conducted a systematic literature review (SLR). A SLR serves to identify potential research gaps in a specific problem area and offers guidance to both practitioners and researchers interested in pursuing further investigations in that field. The SLR methodology entails accessing relevant studies from electronic databases, synthesizing the findings, and presenting them in response to the defined research questions. By conducting an SLR, new perspectives emerge, aiding newcomers in comprehending the current state-of-the-art in the field.

It is crucial for an SLR to be replicable, meaning that all the steps taken must be clearly explained, and the results should be transparent for other researchers to evaluate. Objectivity and transparency are key factors for the success of an SLR [10]. As the name suggests, an SLR necessitates a systematic approach that encompasses all the literature published thus far. This study provides an exhaustive compilation of the existing literature regarding the use of machine learning for smart irrigation system. Additionally, we present our empirical findings and address the research questions defined within this review article. For this systematic literature review we collected all studies that integrated the important technologies used in the process of SIS. Publications between 2017 and 2023 were considered, in which the important technology is machine learning with its different approaches.

The rest of the paper is organized as follows: Section 2 describes the methodology used in this review. Section 3 presents and discusses the review results. Section 4 provides the limitation of this work and Section 5 provides conclusions and future guidelines obtained from this systematic review.

Table 1
Research questions.

RQ#	Research questions	Motivation
RQ1	Which ML techniques have been used in the literature for Smart Irrigation system?	Identify the ML techniques commonly being used in SIS.
RQ2	What is the overall performance of the ML techniques for SIS?	Investigate the performance of the ML techniques for SIS.
RQ3	Do ML models outperform non-ML models?	Investigate the performance of the ML techniques over non-ML models for SIS.
RQ4	Are there any ML techniques that significantly outperform other ML techniques?	Investigate the performance of the ML techniques over the other ML techniques for SIS.
RQ5	What are the strengths and weaknesses of the ML techniques?	Determine the information about ML techniques.

2. Method

The systematic review planning used in this work has been inspired from the SLR process suggested by Kitchenham and Charters [10], the process is detailed in Fig. 1, the important steps of this process:

Research questions identification: we construct the research questions based on the purpose of SLR.

Search strategy design: we described the search strategy to find out the important studies to the research question, this step involves both identification of search terms and selection of sources to be searched in order to identify the initial list.

Study selection criteria: we extract the relevant studies from the initial list by using the inclusion and exclusion criteria that we will identify in the next section, for each primary study in initial list.

Data extraction: we involve the design of data extraction forms to collect the required information in order to answer the research questions

Data synthesis: we determined the proper methodologies for synthesizing the extracted data based on the types of the data and the research questions the data addressed.

A review protocol is of critical importance for an SLR (M [11]). To ensure the rigorousness and repeatability of this SLR and to reduce researcher bias as well, we elaborately developed the review protocol by frequently holding group discussion meetings on protocol design. In the next Subsection, we will present the details of the review protocol. At the end of this section, we will analyze the threats to validity of the review protocol.

3. Research questions

The goal of this SLR is to summarize and clarify the empirical evidence obtained from the studies using the ML techniques for SIS in the literature. Toward this goal five research questions (RQs) were defined as presented in Table 1. From the selected studies we identified the ML techniques used in Smart irrigation system (RQ1), and then we analyzed the performance of the ML techniques for SIS (RQ2). This question fo- cuses on the values of the performance measures for SIS, after that we compare the performance of ML techniques with non-ML techniques (RQ3), The aim of this question is to determine whether ML techniques are better than the statistical techniques. (RQ4) we do a comparison between different ML techniques, whose can be synthesized to deter- mine which ML models consistently outperform other ML models. The final question (RQ5) determines the strengths and weakness of different ML techniques.

4. Search strategy

The detailed description of the search strategies utilized in this research consisted of search terms, literature resources and search pro-

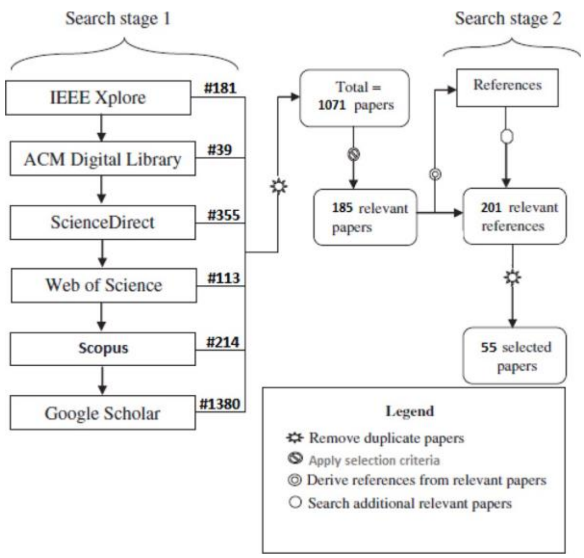

Fig. 2. Search and selection process.

4.1. Search terms

The following steps were used to generate the search terms [12]:

a) Derivation of major terms from the research questions.
b) Identification of alternative spellings and synonyms for major terms.
c) Identification of keywords in relevant papers or books.
d) Usage of the Boolean OR to incorporate alternative spellings and synonyms.
e) Usage of the Boolean AND to link the major terms.

The resulting search terms are described as follows: ("Smart Irrigation" OR "Precision Irrigation") AND ("Machine Learning" OR "Artificial Intelligence")

4.2. Literature resources

The literature resources we exploited to search for primary studies contain six electronic databases:

Ø IEEE Xplore
Ø ScienceDirect
Ø Web of Science
Ø Scopus
Ø Google Scholar
Ø ACM Digital Library

The search terms established previously were employed to search for journal papers and conference papers in the six electronic databases. The search was conducted on the first six databases covering title, abstract, and keywords. For Google Scholar, only title was searched since the full text search will return millions of irrelevant records. We limited the search to the period from 2017 to 2023**,** because the most relevant study of the application of ML techniques in SIS domain was launched just in the early 2017.

4.3. search process

SLR necessitates a comprehensive search of all relevant sources.

- Search stage 1: A thorough search was launched on the six electronic database sources and the returned results (papers) were assembled as sets of prospective papers.
- Search stage 2: The reference lists of all relevant papers were perused to detect additional relevant papers and then, if any, combine them with the ones in stage 1.

Software package Mendeley (https://www.mendeley.com) was used to store and manage the search results. We identified 55 relevant papers according to the search process. The detailed search process and the number of papers identified at each phase are shown in Fig. 2.

5. Study selection

From the first search stage, 1071 prospective studies were realized. Since many of the candidate papers provide no information useful to address the research questions raised by this review, further filtering is needed to identify the relevant papers belong the candidate papers by using the inclusion and the exclusion criteria (defined below). This is exactly what study selection aims to do. Specifically, as illustrated in Fig. 2.

We defined the following inclusion and exclusion criteria, which had been refined through pilot selection. We carried out the study selection by reading the titles, abstracts, or full text of the papers.
That's why, we defined the search process and split it into the following two phases (note that the relevant papers are those papers that verify the selection criteria defined in the next section).

Inclusion criteria:

- Empirical studies using the ML techniques for SIS.
- Empirical studies using at least two ML models for SIS.
- Empirical studies combining the ML and non-ML techniques.
- For duplicate publications of the same study, only the most complete and newest one will be included.
- For study that has both conference version and journal version, only the journal version will be included.

Exclusion criteria:

- Studies without empirical analysis or results of use of the ML techniques for SIS.
- Studies using the ML techniques in context other than SIS.
- Review studies.

Two researchers conducted independent evaluations to test the aforementioned inclusion and exclusion criteria. Through thorough discussions, they arrived at a mutual decision. In instances of uncertainty, the complete texts of the studies were reviewed, leading to a final determination regarding their inclusion or exclusion. Furthermore, any duplicate studies by a specific author with identical results were elimi- nated. Ultimately, a total of 55 studies were selected by employing the aforementioned selection criteria.

6. Data extraction and data synthesis

For each of the selected studies, we completed a form to extract pertinent information. The purpose of using the data extraction form was to identify which research question was addressed by each selected study. The extracted data included details such as author names, titles, publishing information, independent variables (metrics), and the ML techniques employed. By analyzing the data extraction cards, we could determine the specific research questions that each selected study aimed to answer. These cards served as a means to gather information from the selected studies.

Two independent researchers collected the necessary information for each selected study using the data extraction cards. They compared their findings, and in case of any discrepancies, additional researchers were consulted to resolve any disagreements. The resulting data was then saved in an Excel file for future use during the data synthesis process.

Table 2
Publication sources and distribution of the selected studies.

Publication name	Type	Number	Percent
Agricultural Water Management	Journal	10	18
Computers and Electronics in Agriculture	Journal	6	11
Journal of Hydrology	Journal	4	7
Computers,Materials & Continua	Journal	2	4
Sensors	Journal	2	4
Food Quality	Journal	2	4
The Crop Journal	Journal	1	2
PeerJ Computer Science	Journal	1	2
Science of the Total Environment	Journal	2	4
Sustainable Energy Technologies and Assessments	Journal	1	2
remote sensing	Journal	1	2
Heliyon	Journal	1	2
Multimedia Tools and Applications	Journal	1	2
Modern Physics Letters B	Journal	1	2
applied sciences	Journal	1	2
Internet of Things	Journal	1	2
Intelligent Systems	Journal	1	2
Security and Communication Networks	Journal	1	2
Smart Agricultural Technology	Journal	1	2
Energy Reports	Journal	1	2
Journal of Science	Journal	1	2
Agriculture	Journal	1	2
Remote Sensing of Environment	Journal	1	2
Environment, Development and Sustainability	Journal	1	2
IEEE Access	Journal	1	2
International Conference on Computer and Knowledge Engineering (ICCKE)	Conference	1	2
International Conference on Data Analytics for Business and Industry (ICDABI)	Conference	1	2
IEEE International Conference on Signal Processing, Computing and Control (ISPCC)	Conference	1	2
IEEE International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)	Conference	1	2
International Conference on Electronics and Sustainable Communication Systems (ICESC)	Conference	1	2
International Conference on Artificial Intelligence and Data Engineering (ICAIDE)	Conference	1	2
Engineering, Technology & Applied Science Research	Conference	1	2
International Conference on Material Processing and Technology (ICMProTech)	Conference	1	2
ICTACT JOURNAL ON SOFT COMPUTING	Conference	1	2
	Total	55	100

Table 3
Selected studies.

ID	Authors	Title	Citation
S01	[13]	Modeling reference evapotranspiration using extreme learning machine and generalized regression neural network only with temperature data	https://doi.org/10.1016/j.compag.2017.01.027
S02	[14]	Evaluation of random forests and generalized regression neuralnetworks for daily reference evapotranspiration modelling	https://doi.org/10.1016/j.agwat.2017.08.003
S03	[15]	An IoT based smart irrigation management system using Machine learning and open source technologies	https://doi.org/10.1016/j.compag.2018.09.040
S04	[16]	Dynamic Neural Network Modelling of Soil Moisture Content for Predictive Irrigation Scheduling	https://doi.org/ 10.3390/s18103408
S05	[17]	Reference evapotranspiration estimation and modeling of the Punjab Northern India using deep learning	https://doi.org/10.1016/j.compag.2018.11.031
S06	[18]	Capability of crop water content for revealing variability of winter wheat grain yield and soil moisture under limited irrigation	https://doi.org/10.1016/j.scitotenv.2018.03.004
S07	[19]	An efficient employment of internet of multimedia things in smart and future agriculture	https://doi.org/10.1007/s11042–019–7367–0
S08	[20]	Machine Learning based soil moisture prediction for Internet of Things based Smart Irrigation System	https://doi.org/10.1109/ISPCC48220.2019.8988313
S09	[21]	A Hadoop based Framework for Soil Parameters prediction	https://doi.org/10.1109/SITIS.2019.00111
S10	[22]	Random forest techniques for spatial interpolation of evapotranspiration data from Brazilian's Northeast	https://doi.org/10.1016/j.agwat.2019.105905
S11	[23]	Machine learning-based irrigation control optimization	https://doi.org/10.1145/3360322.3360854
S12	[24]	Estimation of daily potato crop evapotranspiration using three different machine learning algorithms and four scenarios of available meteorological Data	https://doi.org/10.1016/j.agwat.2019.105875
S13	[25]	Long short-term memory neural network-based multi-level model for smart irrigation	https://doi.org/10.1142/S0217984920504187
S14	[26]	Smart Irrigation IoT Solution using Transfer Learning for Neural Networks	https://doi.org/10.1109/ICCKE50421.2020
S15	[27]	Improve Irrigation Timing Decision for Agriculture using Real Time Data and Machine Learning	
S16	[28]	IoT based Smart System for Enhanced Irrigation in Agriculture	

The main objective of data synthesis was to combine and consolidate the findings and results from the selected studies to formulate responses and address the research questions. By aggregating studies that presented similar viewpoints and comparable results, we obtained research evidence that contributed to obtaining conclusive answers.

During the synthesis process, we meticulously scrutinized and evaluated both quantitative and qualitative data. The quantitative data encompassed various performance metrics, such as AUC, prediction accuracy, while the qualitative data included the strengths and weaknesses of the ML methods and the categorization of different ML techniques. To address the research questions, we employed visualization techniques, such as line graphs, box plots, pie charts, and bar charts. Additionally, we used tables to summarize and present the results.

7. Results and discussion

This section presents the results obtained from selected studies for smart irrigation system. First, we present the overview of each selected study. Second, the answers to the review research questions are provided in each sub-section. Then we provide the discussion and interpretation of the results in the view of the facts obtained from each selected study.

S17	[29]	Simulating wetting front dimensions of drip irrigation systems: Multi criteria assessment of soft computing models	
S18	[30]	Soil water content and actual evapotranspiration predictions using regression algorithms and remote sensing data	.9303612
S19	[31]	New approach to estimate daily reference evapotranspiration based on hourly temperature and relative humidity using machine learning and deep learning	https://doi.org/10. 1109/ICDABI51230.202 0.9325680 https://doi.org/10.110 9/ICESC48915.2020
S20	[32]	A Deep Learning Approach for Multi-Depth Soil Water Content Prediction in Summer Maize Growth Period	.9156026 https://doi.org/10.10 16/j.jhydrol.2020. 124792
S21	[33]	Short term soil moisture forecasts for potato crop farming: A machine learning approach	https://doi.org/10.10 16/j.agwat.2020.10 6346
			https://doi.org/10.10 16/j.agwat.2020.10 6113
			https://doi.org/ 10.1109/ACCESS.202 0.3034984
			https://doi.org/10.10 16/j.compag.2020.10 5902

(*continued on next page*)

Table 3 (*continued*)

ID	Authors	Title	Citation
S22	[34]	Field Data Forecasting Using LSTM and Bi-LSTM Approaches	https://doi.org/10.3390/app112411820
S23	[35]	Artificial intelligence methods reliably predict crop evapotranspiration with different combinations of meteorological data for sugar beet in a semiarid area	https://doi.org/10.1016/j.agwat.2021.106968
S24	[36]	Soil color analysis based on a RGB camera and an artificial neural network towards smart irrigation: A pilot study	https://doi.org/10.1016/j.heliyon.2021.e06078
S25	[37]	Mapping maize crop coefficient Kc using random forest algorithm based on leaf area index and UAV-based multispectral vegetation indices	https://doi.org/10.1016/j.agwat.2021.106906
S26	[38]	Machine Learning Approach for an Automatic Irrigation system Irrigation System in Southern Jordan Valley	https://doi.org/10.48084/etasr.3944
S27	[39]	Smart Irrigation System for Urban Gardening using Logistic Regression algorithm and Raspberry Pi	https://doi.org/10.1088/1742–6596/2129/1/012044
S28	[40]	IoT-IIRS: Internet of Things based intelligent-irrigation recommendation	https://doi.org/10.7717/peerj-cs.578
S29	[41]	Sustainable Irrigation System for Farming Supported by Machine Learning and Real-Time Sensor Data	https://doi.org/10.3390/s21093079
S30	[42]	An IoT-Based Predictive Analytics for Estimation of Rainfall for Irrigation	https://doi.org/10.1007/978–981–15–3514–7_105
S31	[43]	Estimation of Grapevine Crop Coefficient Using a Multispectral Camera on an Unmanned Aerial Vehicle	https://doi.org/10.3390/rs13132639
S32	[44]	Numerical and artificial intelligence models for predicting the water advance in border irrigation	https://doi.org/10.1007/s10668–021–01453–6
S33	[45]	Estimation of root zone soil moisture from ground and remotely sensed soil information with multisensor data fusion and automated ML	https://doi.org/10.1016/j.rse.2021.112434
S34	[46]	Fusion of Feature Selection Methods and Regression Algorithms for Predicting the Canopy Water Content of Rice Based on Hyperspectral Data	https://doi.org/10.3390/agriculture11010051
S35	[47]	A low-cost approach for soil moisture prediction using multi-sensor data and machine learning algorithm	
S36	[48]	Water optimization technique for precision irrigation system using IoT and machine learning	
S37	[49]	MANAGING IRRIGATION NEEDS BASED ON SMART DECISIONS USING MACHINE LEARNING	
S38	[50]	Irrigation optimization with a deep reinforcement learning model_ Case study on a site in Portugal	
S39	[51]	Soil moisture content estimation in winter wheat planting area for multi-source sensing data using CNNR	
S40	[52]	Application of IoT and Cloud Computing in Automation of Agriculture Irrigation	
S41	[53]	Design-of-Machine-Learning-Based-Smart-Irrigation-System-for-Precision-Agriculture	
S42	[54]	Estimation of soil moisture content under high maize canopy coverage from UAV multimodal data and machine learning	
S43	[55]	Iot with evolutionary algorithm-based-deep-learning-for-smart-irrigation-systemComputers-Materials-and-Continua	
S44	[56]	Nation-scale reference evapotranspiration estimation by using deep learning and classical machine learning models in China	https://doi.org/10.1016/j.jhydrol.2021.127207
S45	[57]	IoT-Driven Model for Weather and Soil Conditions Based on Precision Irrigation Using Machine Learning	https://doi.org/10.1155/2022/7283975
S46	[58]	IoT-enabled edge computing model for smart irrigation system	https://doi.org/10.1515/jisys-2022–0046
S47	[59]	Estimation of transpiration coefficient and aboveground biomass in maize using time-series UAV multispectral imagery	https://doi.org/10.1016/j.cj.2022.08.001
S48	[60]	Spatiotemporal modeling to predict soil moisture for sustainable smart irrigation	https://doi.org/10.1016/j.iot.2022.100671
S49	[61]	Simulation of daily maize evapotranspiration at different growth stages using four machine learning models in semi-humid regions of northwest China	https://doi.org/10.1016/j.jhydrol.2022.128947
S50	[62]	Prediction of maize crop coefficient from UAV multisensor remote sensing	https://doi.org/10.1016/j.agwat.2022.108064
S51	[63]	Machine Learning Techniques for the Classification of IoT-Enabled Smart Irrigation Data for Agricultural Purposes	https://doi.org/10.54287/gujsa.1141575
S52	[64]	Intrusion Detection Using Machine Learning for Risk Mitigation in IoT-Enabled Smart Irrigation in Smart Farming	https://doi.org/10.1155/2022/3955514
S53	[65]	Smart irrigation system based on IoT and machine learning	https://doi.org/10.1016/j.egyr.2022.07.088
S54	[66]	Evaluating soil moisture content under maize coverage using UAV multimodal data by machine learning algorithms	https://doi.org/10.1016/j.jhydrol.2023.129086
S55	[67]	Forecasting vapor pressure deficit for agricultural water management using machine learning in semi-arid environments	https://doi.org/10.1016/j.agwat.2023.108302

https://doi.org/10.10 16/j.scitotenv.20 22.155066

https://doi.org/10.1016 /j.seta.2022.102307

https://doi.org/10.2 1917/ijsc.2022.0353

https://doi.org/10.10 16/j.agwat.2022.10 7480
https://doi.org/10.10 16/j.compag.2021.10 6670
https://doi.org/10.11 55/2022/8285969

https://doi.org/10.3260 4/cmc.2022.022648

https://doi.org/10.10 16/j.agwat.2022.10 7530

https://doi.org/10.3260 4/cmc.2022.021789

8. Overview of selected studies

In this section, we provide the brief description of the selected studies; We identified 55 studies Table 3 which use the ML techniques for SIS. The studies were mostly based on public or open-source data sets. These papers were published during the time period 2017–2023. Among them, 46 (83,64%) papers were published in journals, 9 (16,36
%) papers appeared in conference proceedings. The publication sources and distribution of the selected studies are shown in Table 2. the most publications were in Agricultural Water Management, Computers and Electronics in Agriculture and Journal of Hydrology.

The publication sources and distribution of the selected studies are shown inTable 3. The major publications were in Agricultural Water Management, Computers and Electronics in Agriculture, and journal of Hydrology. The impact factor of these three journals is 6.7, 8.3, and 6.4, respectively. These journals are prestigious in agriculture domain, and 20 (36 %) studies for this review are retrieved from them.

9. Publication years

Fig. 3 introduces the distribution of the studies from the year 2017 to 2023. Fig. 3 shows that the number of studies increases year by year from 2017 onwards, which illustrates the evolution of research in the application of ML techniques for SIS. The number of studies in the years

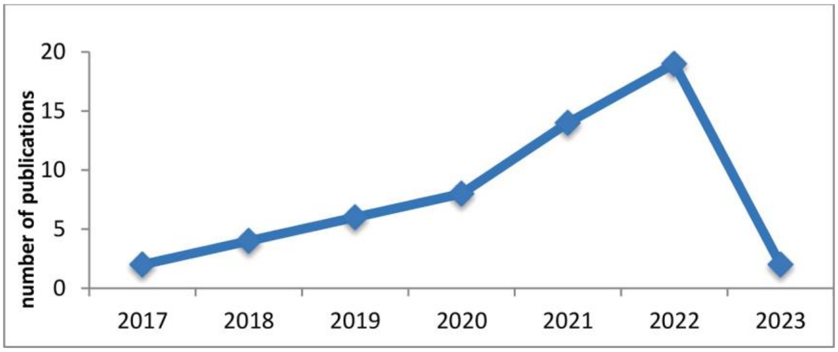

Fig. 3. Number of publications per year.

Table 4
The classification of ML techniques and selected studies of each category.

			# of studies used
Neural networks (NN)	MLP, RBF, CNN, BPNN, FFNN, GRNN, ELM, AFNN, LSTMNN, DQNN	S01, S02, S04, S05, S06, S07, S09, S10, S11, S12, S13, S14, S15, S19, S20, S21, S22, S24, S26, S29, S31, S33, S34, S36, S38, S39, S41, S42, S44, S49, S50, S51, S53	33
Support vector machines (SVM)		S06, S07, S10, S12, S13, S15, S16, S21, S23, S28, S29, S35, S37, S40, S41, S43, S49, S51, S52, S53	20
Fuzzy & Neuro Fuzzy based (NF)		S09, S10,	2
Clustering (CL)	K-Means	S03, S46	2
Instance Based (IB)	KNN	S12, S16, S23, S30, S37, S41, S42, S45, S53, S54	10
Decision trees (DT)	M5P, REPTree, CART, ART	S13, S28, S29, S30, S43, S45, S46, S55	8
Bayesian learners (BL)		S16, S28, S37, S40, S43, S45, S53	7
Ensemble learners (EL)	RF, RSS, GBT, Boosting	S02, S05, S07, S08, S12, S13, S15, S17, S18, S19, S20, S21, S23, S25, S29, S30, S31, S33, S34, S35, S36, S40, S42, S46, S47, S49, S50, S51, S52, S54, S55	31
Evolutionary algorithms (EA)	GA, GEP	S17, S31, S32	3
Miscellaneous (Misc)	WINSRFR, GBRT, XGBR, GL,HG, Arima, Calibrated-HG	S01, S08, S09, S31, S32, S35	6

2018, 2019, 2020, 2021 and 2022 were 3, 6, 8, 12 and 19, respectively accounting about 70.9 % of the studies between 2020 and 2022. For year 2023, data is not complete as the search was finished in june 2023 and only few studies were online till then.

10. RQ1: which ml techniques have been used in the literature for SIS?

In this section, we outline the ML techniques employed in the selected studies gathered during this systematic literature review (SLR). Through careful analysis of the selected studies, we have categorized the ML techniques used for SIS, as follows:

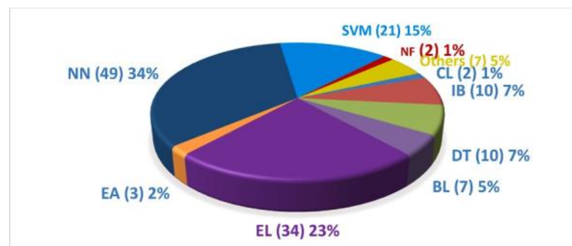

Fig. 4. Distribution of the studies over type of ML technique.

- Neural networks (NN)
- Support vector machines (SVM)
- Fuzzy & Neuro Fuzzy based (NF)
- Clustering (CL)
- Instance Based (IB)
- Decision trees (DT)
- Bayesian learners (BL)
- Ensemble learners (EL)
- Evolutionary algorithms (EA)
- Miscellaneous (Misc)

Table 4 introduces the classification of ML techniques for SI used in this SLR and the studies that used them

Among the above listed categories of the ML techniques the most frequently used techniques were from categories NN, SVM and EL adopted by 72 % of selected studies, as illustrated in Fig. 4. These ML techniques were used for SIS. The identified ML techniques were used to evaluate SIS usually in two forms: (1) studies comparing ML techniques (2) studies comparing statistical and ML techniques; Fig. 3 is plotted to further outline the distribution of research interest in each publication year. As can be seen, the activity of publications in this field is growing at an explosive rate. Note that some studies contain more than one ML technique.

As shown in Fig. 5, for one thing, an apparent publication peak is shown in 2022; Moreover, compared to other ML techniques, SVM, NN and EL seem to have received dominant research attention in many years. It is noteworthy that in neural network studies, both traditional Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs) have been considered for this review. Deep learning methods can be seen as an improved extension of the classic ANNs consisting of more layers that enable higher degrees of abstraction and enhanced assess- ment from data. An example can be seen in study done by flan et al.[ref] in which they use Unet architecture for optimizing irrigation system in a small green house for tomato crops.

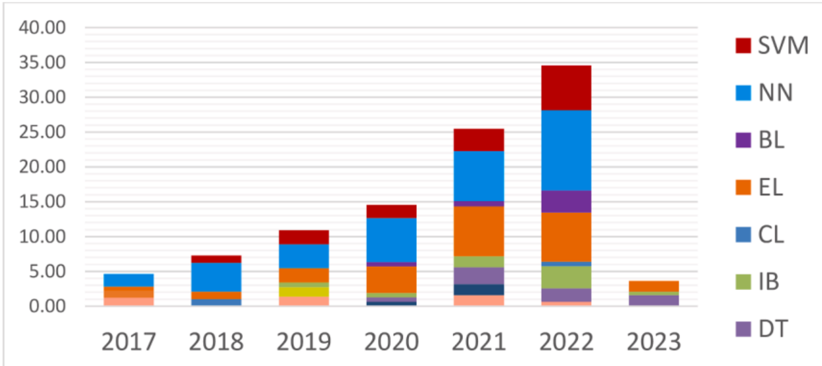

Fig. 5. Distribution of the studies over publication year.

Table 5
Performance metrics used in studies.

Performance metrics	Studies
accuracy	**S05, S13, S15, S16, S26, S27, S28, S29, S34, S37, S40, S41, S43, S45, S46, S48, S51, S52, S53.**
RMSE	**S04, S05, S06, S09, S12, S18, S19, S20, S21, S22, S23, S25, S30, S31, S32, S33, S35, S36, S38, S39, S42, S44, S47, S50, S53, S54, S55.**
R^(2)	**S03, S04, S05, S06, S08, S09, S10, S11, S12, S18, S19, S21, S23, S25, S31, S32, S34, S35, S36, S38, S39, S42, S44, S46, S47, S50, S54.**
MAE	**S01, S02, S04, S09, S10, S11, S12, S18, S20, S21, S23, S31, S32, S44, S55.**
MSE	**S03, S05, S08, S11, S12, S14, S20, S23, S24, S26, S46, S49.**
Precission	**S07, S13, S26, S28, S37, S41, S43, S51.**
Recall	**S07, S13, S26, S28, S37, S41, S43, S51.**
F1-Score	**S07, S13, S26, S41, S43, S51.**
NSE	**S05, S18, S19, S44.**
NS	**S01, S02, S17.**
SI	**S10, S17, S32.**
Miscellaneous (EVS, AUC, RRSE, EF, R)	**S03, S11, S12, S13, S55.**

11. Rq2: what is the overall performance of the ml techniques for SIS?

The primary objective of this systematic literature review (SLR) is to explore the utilization of machine learning (ML) algorithms in SIS. The intention is to offer valuable insights to future researchers and practitioners engaged in SIS studies. To achieve this, an extensive investigation has been under taken to understand how ML algorithms are applied in SIS, focusing on the performance measures employed by researchers to assess the reliability and effectiveness of the developed ML models in real-world applications. The utilization of validation methods, such as n-fold Cross-Validation ($n > 1$) and Leave-One-Out Cross-Validation (LOOCV), has been analyzed, and it has been observed that 22 studies used k-fold Cross-Validation, while 2 studies used LOOCV.

Apart from validation methods, various metrics have been employed to evaluate the performance of ML approaches in SIS. These metrics are crucial for comparing and evaluating models developed using diverse ML and statistical techniques. It is worth noting that a single algorithm may utilize multiple metrics to describe its performance. Therefore, selecting appropriate accuracy metrics for evaluating estimation accuracy is essential. Table 5 provides an overview of the performance metrics used and the studies in which they were applied. Additionally, the distribution of studies using each performance metric is illustrated in Fig. 6. The most popular metrics found in the selected studies are Accuracy, RMSE, and R-Squared, with adoption rates of approximately 34.55 %, 49.09 %, and 45.45 %, respectively. Other commonly used metrics include MAE, MSE, Precision, Recall, and F1-Score. Less commonly employed measures are categorized under miscellaneous metrics, including EVS, AUC, RRSE, EF and R.

The analysis of evaluation measures reveals their popularity and introduces other metrics to researchers. However, given the dominance of Accuracy, RMSE, and R-Squared metrics, we have chosen to adopt them in this review for evaluating the performance of ML models. These metrics are crucial in determining the accuracy of the estimates. To gain insight into the distribution of these metric values for ML techniques, we have utilized box plots in Fig. 5a–c, respectively. Nevertheless, in cases where the number of observations for the selected metrics in certain ML categories is small, we have refrained from including them in the figures

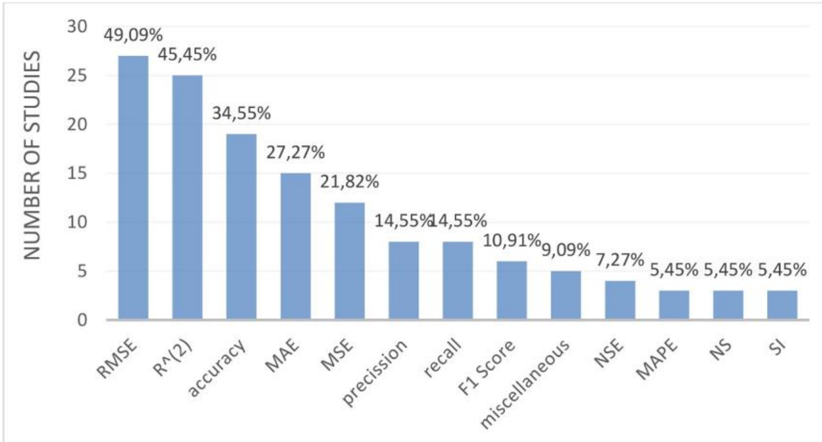

Fig. 6. Distribution of the studies over performance metrics.

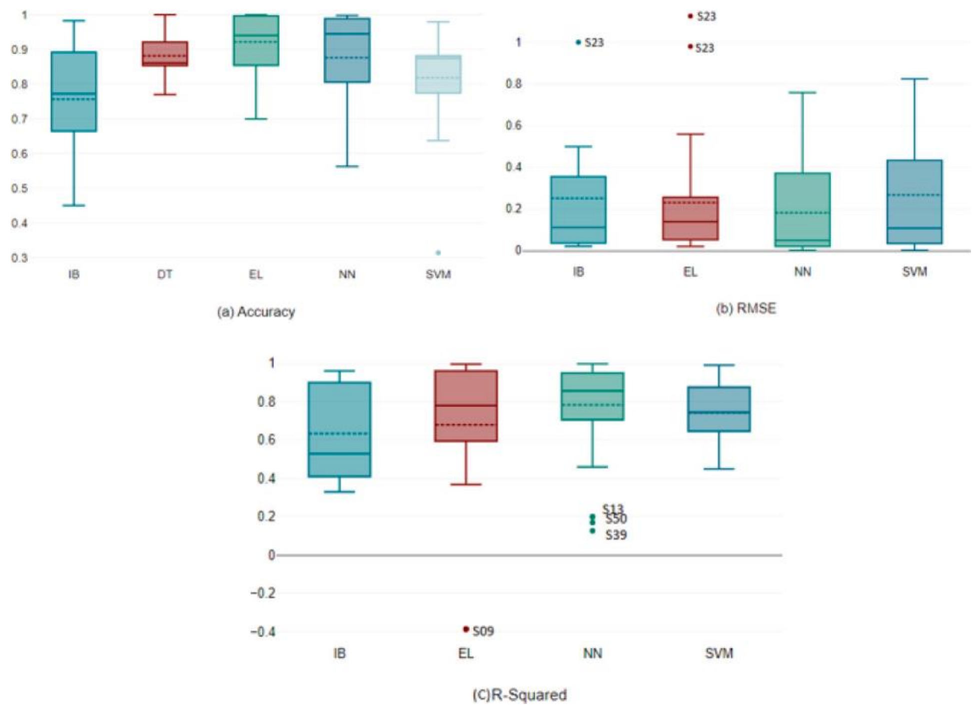

Fig. 7. Box plots of Accuracy, RMSE and R-Squared (outliers are labeled with associated study IDs).

Table 6
Comparisons of R-Squared between ML models and non-ML models (‘‘**+**’’ indicates ML model outperforms non-ML model, ‘‘**–**’’ indicates non-ML model outperforms ML model; the number following study ID is RMSE improvement in percentage, the study ID in bold indicates the improvement exceeds 2%).

ML-Model		Non-ML Model			
		SVR	PLSR	MLR	naive
NN	+	**S11(50),** S39 (0.08), **S39 (2.45),** S39 (0.82)	**S06(42.86), S34(3.93), S34 (7.27), S34 (4.03), S34 (6.97), S34 (8.6)**	NA	**S04(6.74), S04(7.95), S04(7.6), S04 (5.62), S04 (10.23), S04 (7.6)**
	–	**S39(31.57), S39(4.56), S39(404), S50(94.11), S50(25.53)**	**S06(10.71), S34(4.44)**	NA	NA
IB	+	NA	**S54(35.29), S54(60.60)**	NA	NA
	–	NA	**S42(64.70), S42(63.64)**	NA	NA
EL	+	**S47(16.67), S50(72.72), S50(16.95)**	**S34(5.53), S34 (8.5), S34 (8.03), S34 (5.41), S34 (6.97), S34 (8.49), S42 (39.29), S42 (44.44), S54 (28.26), S54 (13.21)**	**S25(97.44), S25(100), S25(78.57), S25 (182.61)**	NA
	–	NA	NA		NA
SVM	+	NA	NA	NA	NA
	–	NA	S06(1.72), **S06 (60)**	NA	NA

As can be seen in Fig. 7 for accuracy demonstrates higher values of performance in terms of NN and EL (with median around 0.95), followed by SVM and DT around 0.87 value, while IB was the least performant

to avoid presenting insignificant data points in a box plot.

with 0.78 value. As for RMSE, approximately all the four models (SVM, NN, EL and IB) have their medians around 0.3, With regard to R-Squared, EL and NN are more efficient (with median around 0.87), followed by SVM (with median around 0.74), then lastly IB with a me- dian around 0.53. In addition to the aforementioned observations, (EL, NN, SVM) for R-Squared all have their median nearly in the centers of the boxes, which implies that the values of these models are symmet- rically distributed around the medians.

12. Rq3: ml models vs. non-ML models

The ML models have been compared with four conventional non-ML models: multiple linear regression, naïve [36], partial least squares regression [19] and support vector regression [10]. The details of the comparisons between ML models and non-ML models are provided in (Table 6), One model is alleged to outperform another in experiment if the R-Squared value of the first model achieves at least 2 % improve- ment comparing to the second one. It was observed that only 18 % of studies compared Non-ML and ML models (10 out of 55). among the four non-ML models, PLSR model is the one used most frequently in com- parison with the ML models.

Fig. 8 indicates the overall results of the comparisons between ML models and non-ML models, where all the comparisons were in terms of R-Squared metric. The bars above zero line indicate that ML models are more accurate, whereas the bars below zero line indicate that non-ML models are more accurate. the majority of the experiments indicate that ML models outperform non-ML models.

Specifically, Fig. 8 shows that 76 % (35 of 46) of experiment results exhibit the superiority of ML models whereas only 24 % (11 of 46) of experiment results exhibit the superiority of non-ML models (note that some studies conduct more than one experiment). The comparison re- sults show that the EL and NN are the most commonly used techniques in the literature; they outperform the PLSR model in 100 % and 75 % of experiments respectively, and these observations are sustained by a number of experiments, while PLSR model outperforms SVM model. For IB, it is hard to determine whether it is more accurate than PLSR model or not, because the number of experiments reporting that IB out- performed regression model is equal to that of experiments reporting the

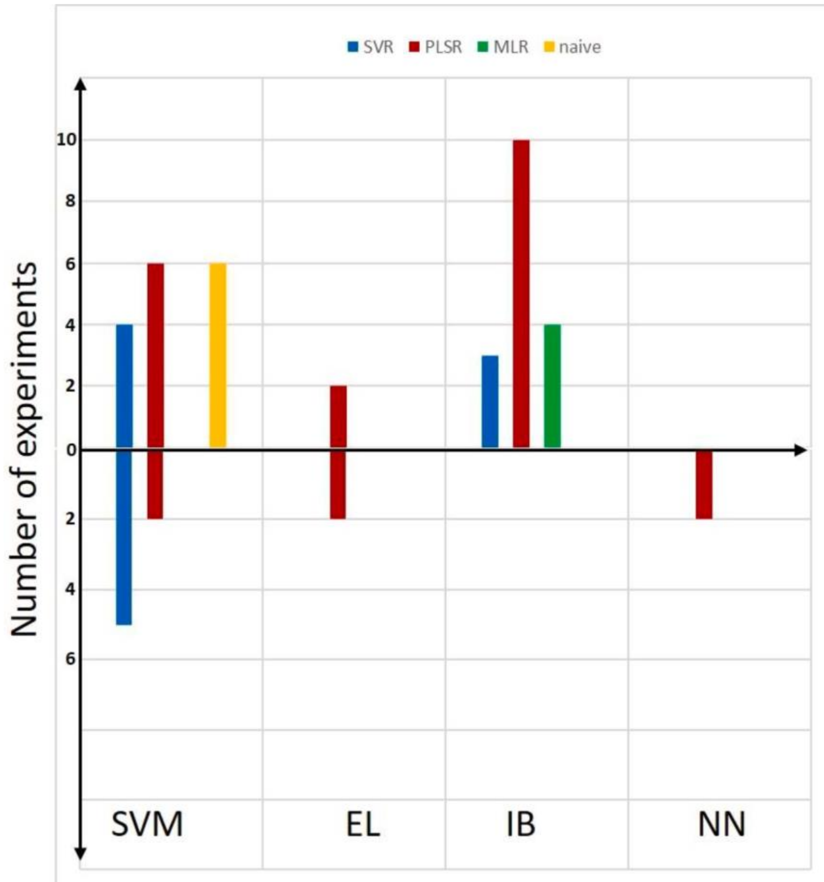

Fig. 8. Comparisons of R-Squared between ML models and non-ML models.

opposite results. In addition to PLSR model, other non-ML models have also been compared with some ML models; EL outperforms SVR model while the last one outperforms NN, With regard to the MLR and naive models, although every model are 4 and 6 experiments, respectively. All the trials of MLR model are less accurate than EL model, also the trials of naïve models are less accurate than NN, in general, the ML models outperform the non-ML, However, there is a threat to the validity to this conclusion as this argument holds only for the three ML models (NN, IB, EL) vs. PLSR and (NN and EL) vs. SVR, which have been supported by a sufficient number of experiments; while it is difficult to fully validate and generalize the conclusions for the other evaluations due the small number of experiments comparing the performance of ML models with the non-ML models. Thus, more number of studies comparing ML models and other models for SIS should be conducted in order to procure satisfactory and generalized results.

13. Rq4: ml models vs. other ml models

As for the comparisons between different ML models, we adopted the same analysis scheme as that used in the comparisons between ML models and non-ML models. That is, the comparisons were conducted on the same experiments in terms of R-Squared metric; one ML model is considered to outperform another in an experiment if it achieves at least 2 % improvement in estimation accuracy.

Fig. 9 shows the overall results of the comparisons between different ML models, together with the corresponding number of supporting experiments. The bars above the zero-line depict the percentage of datasets in which the ML technique outperforms the other ML techniques. The bars below the zero-line were only used when the ML technique did not outperform the other ML techniques in any of the dataset. More details of the comparison results can be found in Table 7. Three significant comparison results can be found in Fig. 9. First, SVM and EL are more accurate than NN, and it is supported by most of the experiments conducting the comparisons. Second, for the case of SVM vs. EL, SVM seems more accurate than EL. Third, for the comparisons between other ML models, the number of experiments is relatively small, and some comparisons are even found to be inconsistent. Therefore, for these ML models that are rarely compared with each other, it is difficult to determine which is more accurate.

14. Rq5: strengths and weaknesses of ml models

Selecting the appropriate ML models for the SIS contexts can be addressed by investigating the candidate ML models from their characteristics, which are generally outlined by the strengths and weaknesses of the ML techniques as recorded by researchers. Hence, the strengths and weaknesses of the ML techniques supported by more than one study are introduced in this section and the detailed information is presented in Table 8. The RF technique has been reported to exhibit good performance in defect prediction problems and is also good in handling multiple datasets with varying properties. The SVM has been applauded for its excellent ability to deal with the redundant features and high-dimensionality. NN works reliably with noisy data and has been proven to hold strong generalization and learning ability as well as adaptability.

Summarily, different techniques have different pros and there is not a one size fits all solution to the problem of SI in form of a ML technique. It all depends on the domain of application; in a situation where false positives are fatal would favor some techniques in comparison to a sit- uation where cost is a factor.

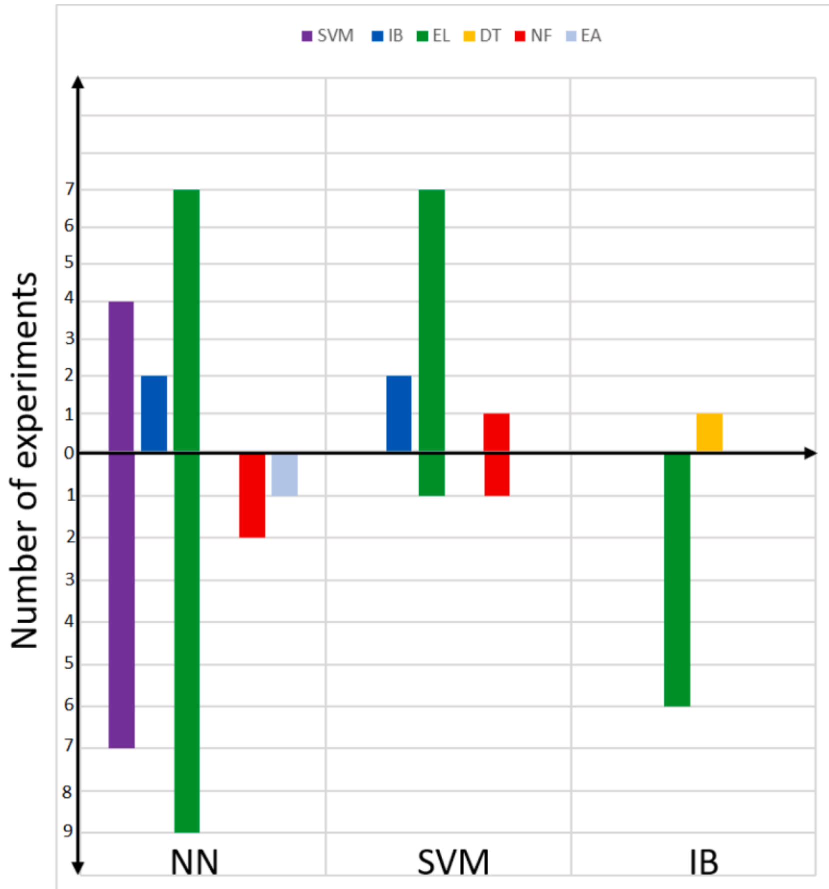

Fig. 9. Comparisons of R-Squared between ML models.

15. Limitation

When interpreting the results of this SLR, some limitations should be captured. Of note, This systematic review considered a number of selected studies to evaluate and assess the performance of various ML models amongst themselves and with Non-ML model. A limitation in this review is that only 23 out of the 55 selected studies compare Non-ML and ML models, Thus, the ML vs non-ML comparison is not definitely conclusive. Also, while comparing ML techniques, various experimental settings are likely to be used by each study, which include validation methods, feature selection methods and pre-processing methods to remove outliers [68], Furthermore, this review considered only the metrics of Accuracy, RMSE, and R-Squared when evaluating the performance of ML models or comparing ML models with other models as they are among the most important ones and were used by most of the studies. However, considering other performance metrics such Precision, Recall, and F1-Score which were ignored in this review, could be a valuable addition to the analysis strategy. finally, this review does not include any unpublished research studies. We have assumed that all the studies are impartial, however if this is not the case then it poses a threat to this study.

16. Conclusion and future guidelines

In this paper we perform a systematic literature review in order to analyze and assess the performance of the ML techniques for smart irrigation system (SIS). First, after a thorough analysis by following a systematic series of steps, we identified 55 selected studies (2017–2023). Second, we summarized the characteristics of the selected studies based on metrics reduction techniques, metrics, and performance measures. Third, we assessed the performance of the ML techniques for smart irrigation system. Fourth, we compared the performance of models predicted using the ML techniques with the models predicted using non-ML techniques. Then, we analyzed the performance of these predicted models using the ML techniques with other ML techniques. Finally, we summarized the strengths and weaknesses of the ML techniques. The main findings obtained from the selected primary studies are:

- (Rq1) The ML techniques were broadly categorized into Decision Tree, Bayesian Learning, Ensemble Learning, Evolutionary Algorithms, Neural Networks, Fuzzy & Neuro Fuzzy based, Clustering, Instance Based and Miscellaneous. The most frequently used ML techniques for Smart Irrigation system were artificial neural networks, Support Vector Machines and Random Forest.
- (Rq2) The results depict that Accuracy, RMSE, and R-Squared are the most commonly used performance measures in the selected studies.
- (Rq3) ML model is more accurate than non-ML model in general, which is supported by most of the studies. PLSR model is the non-ML model that is most often compared with ML models.
- (Rq4) Both SVM and EL are less accurate than NN, which are sup- ported by most of the studies conducting the comparisons.
- (Rq5) Every ML technique have different strengths and weaknesses.

This review provides recommendations for researchers as well as guidelines for practitioner to carry out future research on Smart irrigation system using the ML techniques:

- More number of studies for Smart Irrigation system should be carried out using the ML techniques in order to obtain generalizable results

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Table 7
Comparisons of R-Squared between different ML models (''**+**'' indicates the model given in the row outperforms the model given in the column, ''-'' indicates the model given in the column outperforms the model given in the row; the number following study ID is R-Squared improvement in percentage, the study ID in bold indicates the improvement exceeds 2 %).

ML		ML					
		SVM	IB	EL	DT	NF	EA
NN	**+**	**S06 (2.17)**, S49 (0.55), S49 (1.39), S10 (1.26)	**S12 (2.71), S12 (2.39)**	S34(0.1), S49(0.28), S49(1.1), S49(1.16), **S49(7.66), S05(3.13), S05(2.05)**	NA	NA	NA
	–	**S06 (9.43),** S06 (1.18), **S49 (5.32), S49 (6.57),** S49 (1.31), S49 (0.13), S10 (1.18)	NA	S34(1.53), **S34 (13.31),** S34(0.70), S34(1.33), **S50 (235.29), S50 (46.80), S36(2.06), S49(4.23)**, S49(0.26)	NA	S10 (0.86), **S10 (21.88)**	S32 (1.68)
SVM	**+**	NA	**S23 (5.94), S23 (3.22)**	**S23(5.19), S23(3), S23 (11.64), S23(3.44), S35 (33.97), S49(1.05), S49(7.8)**	NA	S10 (0.32)	NA
	–	NA	NA	S49(0.28),	NA	**S10 (23.42)**	NA
IB	**+**	NA	NA	NA	**S30 (9.57)**		NA
	–	NA	NA	**S42 (129.41), S42 (136.36), S54 (73.53), S54 (81.81),** S23 0.71), S23(0.21)	NA	NA	NA

and gain more proof on the viability of ML models. As there are few studies that compare the ML techniques with the non-ML techniques, more studies should compare the performance of the ML techniques with non-ML techniques.

- There are very few studies that examine the effectiveness of evolutionary algorithms such as GP, ACO for Smart Irrigation system. The future studies may focus on the predictive accuracy of evolutionary algorithms for Smart irrigation system.
- The ML techniques should be carefully selected based on their properties. Before making the decision of selection of a ML technique, the characteristics of the ML technique should be understood completely by the researcher.
- ML models should be adopted in parallel with existing conventional models at the early stage in order to unlock the true potential of a given ML technique.
- The study should clearly specify the parameters values for the respective ML techniques used so that the framework in the studies

Table 8
Strengths and weaknesses of ML techniques.

Technique name	Strengths	Supporting studies
RF	It can handle large data and are consistent performers.	**S34** **S50**
	Fast to train, robust towards parameter setting.	**S34, S49.** **S50, S35.**
	Provide understandable model.	**S49, S35.**
	Runs efficiently on large data sets.	
	Helps in identifying most important independent variables.	
SVM	Good tolerance for high-dimension space and redundant features.	**S06, S23** **S06, S10**
	Robust in nature.	**S49, S23**
	It can handle complex functions.	**S23, S06, S10**
	It can handle nonlinear problems.	
NN	Hold strong generalization and learning ability as well as adaptability.	**S05** **S34, S12**
	Can do fast real-time computation with better computational efficiency.	**S35** **S49**
	Can avoid over-fitting.	
	Capable of dealing with noisy data	
KNN	Intuitive and easy to understand	**S12**
	Robust in nature	
Technique name	**Weaknesses**	**Supporting studies**
SVM	It has very limited success when applied to imbalanced data sets.	**S49**
	Choosing an adequate kernel function.	
NN	Require diversified training data set to train the model effectively.	**S05, S50** **S06, S10**
	Cost large computational resource.	

CRediT authorship contribution statement

Abiadi Younes: Formal analysis, Funding acquisition, Writing – original draft, Writing – review & editing. **Zouhair Elamrani Abou Elassad:** Supervision, Validation. **Othmane El Meslouhi:** Supervision, Validation. **Dauha Elamrani Abou Elassad:** Resources. **Ed-dahbi Abdel Majid:** Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

can be successfully repeated by the software community.

Data availability

No data was used for the research described in the article.

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